https://doi.org/10.31436/iiumej.v24i2.2814

EYE BLINK IDENTIFICATION AND REMOVAL FROM SINGLE-CHANNEL EEG USING EMD WITH ENERGY THRESHOLD AND ADAPTIVE FILTER

LUTFI AIZAT MOHAMED JEFRI, FARIDAH ABD RAHMAN*, NOREHA ABDUL MALIK AND FARAH NADIA MOHD ISA

Dept. of Electrical and Computer Engineering, International Islamic University of Malaysia, Kuala Lumpur, Malaysia

**Corresponding author: faridah_ar@iium.edu.my*

(Received: 7 April 2023; Accepted: 31 May 2023; Published on-line: 4 July 2023)

ABSTRACT: Electroencephalography (EEG) is a non-invasive method for measuring electrical activity in the brain, which reflects the underlying neural activity of the brain. In recent years, portable EEG devices become more ubiquitous in domestic uses, research and clinical applications due to their compact design and ease of use in various settings. Like many other bio signal modalities, EEG devices are prone to the interference of physiological artifacts, mainly from eye blinking. However, since portable EEGs are equipped with only a few channels at most or sometimes just contain a single channel, removing the eye blink artifact from the EEG data is a challenge. The conventional artifact removal method using source separation cannot be applied to a single-channel EEG signal. Eye blink artifact removal is important because its spectrum overlaps with the EEG's theta and delta frequency bands, which can be confused with brain activity. Univariate-based removal method is compatible with EEG data with few channels. This paper presents a method to remove eye blink artifact based on single-channel EEG processing using Empirical Mode Decomposition (EMD) and Adaptive Noise Cancellation (ANC) system. By applying energy thresholds in EMD, there is no need to incorporate EMD with other methods to extract eye blink component accurately. ANC is used to converge the extracted eye blink component for effective eye blink artifact removal with very minimal changes to affected EEG data. The proposed method was tested on simulated EEG signals, and the result showed a good Root Mean-Square Error (RMSE) average value of the cleaned EEG (0.3211 ± 0.2738) and a high Correlation Coefficient (CC) average value of the cleaned EEG (0.9430 ± 0.0839).

ABSTRAK: Electroensefalografi (EEG) adalah kaedah bukan invasif untuk mengukur aktiviti elektrik di dalam otak, yang mencerminkan aktiviti saraf dalam otak. Kebelakangan ini, peranti EEG mudah alih menjadi lebih meluas dalam kegunaan domestik, penyelidikan dan aplikasi klinikal kerana reka bentuknya yang padat dan kemudahan penggunaan dalam pelbagai tetapan. Seperti kebanyakan modaliti biosignal yang lain, peranti EEG terdedah kepada gangguan artifak fisiologi, terutamanya daripada kerdipan mata. Walau bagaimanapun, memandangkan EEG mudah alih dilengkapi dengan paling banyak pun hanya beberapa saluran, atau kadangkala hanya satu saluran, mengalih keluar artifak kerdipan mata daripada data EEG adalah satu cabaran. Kaedah penyingkiran artifak konvensional menggunakan pemisahan sumber tidak dapat digunakan pada alat EEG satu saluran. Penyingkiran artifak kerdipan mata adalah penting kerana spektrumnya bertindih dengan jalur frekuensi teta dan delta EEG, maka boleh dikelirukan dengan aktiviti otak. Kaedah penyingkiran berasaskan univariat adalah serasi untuk data EEG dengan saluran yang sedikit. Kertas kerja ini membentangkan kaedah untuk membuang artifak kelipan mata berdasarkan pemprosesan EEG saluran tunggal menggunakan Penguraian Mod Empirikal (EMD) dan Pembatalan Bunyi Adaptif (ANC). Dengan menggunakan ambang tenaga dalam EMD, tiada keperluan untuk menggabungkan EMD dengan kaedah lain bagi mengekstrak komponen kerdipan mata dengan tepat. ANC digunakan untuk menumpu komponen kerdipan mata yang diekstrak bagi penyingkiran artifak kerdipan mata yang berkesan dengan perubahan yang sangat minimum pada data EEG yang terjejas. Kaedah yang dicadangkan telah diuji pada signal EEG yang disimulasi, serta hasilnya menunjukkan nilai purata Ralat Min Kuasa Dua Purata (RMSE) yang baik bagi EEG yang dibersihkan (0.3211±0.2738), dan nilai purata Pekali Korelasi (CC) yang baik bagi EEG yang dibersihkan (0.9430±0.0839).

KEY WORDS: *Adaptive Filter, Eye Blink Extraction, EMD, Energy Thresholding, Univariate Processing*

1. INTRODUCTION

Electroencephalography (EEG) is one of the brain monitoring modalities that records electrical signals that originate from the neuronal activities across the cerebral cortex of the brain. These signals correspond to the higher level of the brain functions such as thinking, solving problems, memory, learning, feeling and processing emotions, intelligence, behavior regulation and body movement to some extent. As such, coupled with EEG equipment that is mainly easy to be used, there are many types of research on the matter related to the brain, utilizing EEG as a medium or small input data to analyze and explore the exactitude of a hypothesis and to synthesize solution for the objective of the research. For example, Jacobsen et al. use EEG to study EEG's beta power variability that corresponds to gait movement variability down the terrain [1]. The design of the EEG equipment is relatively of simpler implementation, making it possible to be miniaturized into a compact and portable EEG device [2]. Likewise, the nature of portable EEG that is simpler and less cumbersome to be set up than medical-grade EEG, making it stand out for use. As such, the interest in incorporating the portable EEG device into brain related research and application development is becoming increasingly ubiquitous [3]–[5]. A review of different brands of portable EEG is also made of their respective efficacy on different domains of brain related study [6]. The application of EEG in research and domestic use is expected to remain ubiquitous.

EEG signals propagate from the cerebral cortex, an outer layer of the brain, then across the meninges, skull, and scalp of the subject to the EEG electrodes, making them prone to contamination with other signals that are not of brain origin, which are called artifacts. These artifacts may be external, meaning they originate from the EEG equipment like electrical interference and alternating current artifact, or internal, meaning signals that originate from a physiological body such as electrooculogram (EOG), electromyogram (EMG) and electrocardiogram (ECG). Although the internal artifacts are of physiological origin, these signals may not be desirable for brain-related analysis because they are not implicative to brain activity during the EEG recording session. Hence, in most cases, artifacts need to be discarded in order to obtain clean, pure EEG data. Unlike internal artifact, external artifacts contamination can be avoided by correct equipment set up. While internal artifacts prevention is accomplished by limiting the subject movements and making sure the subject is calm during EEG recording. Likewise, there have been many techniques being proposed on how to remove these internal artifacts. Nevertheless, eye blinks are considered one of the most pervasive artifacts contaminating the EEG signals. Eye blink artifact is persistent in its presence during EEG recording even with restrictive and controlled experimental design. Ultimately, there would be many scenarios where eye blink artifact removal comes in handy when it comes to EEG recording.

Therefore, with relation to portable EEG, the univariate-based eye blink removal method is preferred compared to the multivariate-based method. This is because the portable

https://doi.org/10.31436/iiumej.v24i2.2814

EEG is only equipped with a few EEG channels. Univariate refers to a single EEG channel use, while multivariate refers to the use of multiple EEG channels. The multivariate-based method generally needs a larger number of inputs as its performance is linearly proportional to the number of inputs. Therefore, the univariate method is more effective than the multivariate method in processing EEG data retrieved from portable devices as it only needs one input to perform effectively. The univariate method also needs to be able to remove the eye blink without affecting the EEG component that is superimposed with the eye blink artifact while maintaining its quality of being straightforward in terms of implementation.

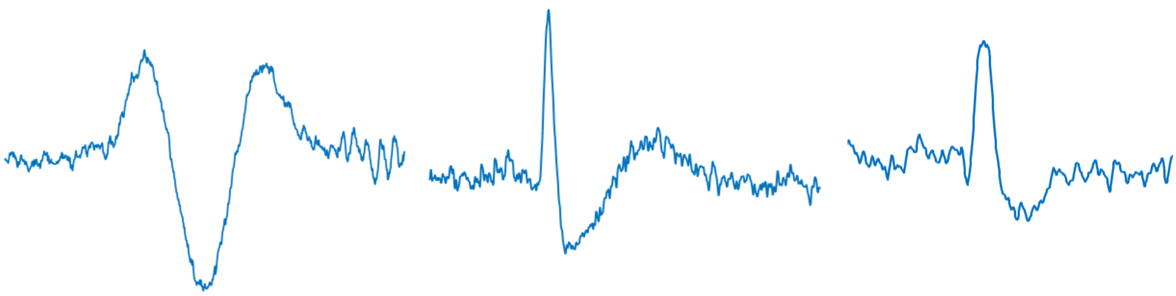
In this paper, we propose a method of eye blink region identification using five samples window-mean and an energy thresholded-Empirical Mode Decomposition (EMD) to extract the eye blink component, coupled with Recursive Least-Mean Square (RLS) adaptive filtering to remove the eye blinks from single-channel EEG. The proposed method aims to approximate the eye blinks artifact within the identified eye blink region with high similarity as a reference in the adaptive noise cancellation system.

2. RELATED WORKS

In this section, a few univariate eye blink removal methods are briefly reviewed, along with the basis of the proposed technique is elaborated. These includes the eye blink detection method, eye blink component extraction and eye blink artifact filtering.

2.1 EEG Eye Blink Artifact Detection

Eye blink artifact is constituted of the overlapped frequency spectrum with EEG theta and delta frequency band (0.3 Hz to 7 Hz) that is indicated by 10 to 100 times bigger amplitude-wise deflections within the EEG data [7]. Occurrences of eye blink artifact contamination in EEG data can be traced by abrupt prominent EEG magnitude change. Therefore is a foolproof way of detecting the eye blink artifact. This is because the propagation of potential from corneal-retinal dipole by the eye lid during eye blinking activity exhibits abrupt deflective spikes in EEG recording [8]. The specific EEG recording brand may influence the temporal characteristic of the deflections. For example, a voluntary eye blink artifact captured using an OpenBCI amplifier, as shown in Fig. 1. (a) has different morphology when compared to an eye blink artifact that is captured using g.Tec amplifier in Fig. 1. (b), and Emotiv device in Fig. 1. (c).



(a) (b) (c)

Fig. 1. Example of voluntary eye blink captured in frontal channel of three different EEG devices (a) OpenBCI, (b) g.Tec cap-type device, (c) Emotiv

Nevertheless, the consistency of the recorded eye blink artifact characteristic across any EEG equipment brand is shown temporally by the huge deflective spike in any EEG data that contains the eye blink artifact. As such, most eye blink detection methods use amplitude-based quantification as means for non-eye blink and eye blink region segregation. This may be in terms of windowed amplitude mean as proposed by authors of [9], highest amplitude as reference for eye blink temporal span approximation as posited in [7], amplitude power, as demonstrated in [10], and amplitude energy as being presented in [11].

Therefore, amplitude-based quantification is suitable to be incorporated in detecting the EEG segment of interest. For the proposed method in this paper, amplitude-based thresholding based on five samples window-mean is used to gauge the EEG data amplitude differences to dismiss the samples with amplitude lower than the threshold but retain the samples that are higher than the threshold to mark the eye blink region, as being demonstrated in [12]. This approach is independent of any assumption on the duration of the eye blinking activity to avoid including clean EEG region with the identified eye blink region or excluding any portion of the eye blink region.

2.2 Eye Blink Component Extraction

Decomposition-based univariate signal processing is a popular class of methods for eye blink removal. Lately, Singular Spectrum Analysis (SSA), with various implementation designs, has been proposed to remove eye blink artifact from a single EEG channel. However, the number of components or subspaces that an input can be composed into must be preset by mapping the single-channel EEG into a multivariate data matrix before decomposition by SSA is executed. Subsequently, the appropriate workaround is introduced to ensure satisfactory eye blink component reconstruction. For example, Maddirala et al. use Hjorth mobility as a threshold to choose the SSA subspaces for the eye blink reconstruction [13]. While in [14], the eigenvalue ratio is used as the threshold to select the subspaces that correspond to the eye blink component for eye blink reconstruction. Nevertheless, different temporal lengths of the recorded EEG and also possibly inconsistent morphology of the eye blink artifact due to different use of EEG devices may cause the variability on the suitable number of subspaces (M) to be preset for the signal decomposition that yields good component separation, which ultimately, causes variability to the threshold value for SSA subspaces selection. The ambiguity of the value that needs to be used in the parameters setting requires preparatory testing, which may complicate the implementation of the proposed methods. In contrast, EMD may bypass this problem for its empirical way of decomposing a signal. Therefore, EMD is adaptable to variable eye blink morphology and EEG temporal length without any respective parameters' adjustment.

EMD is a data-driven method that decomposes signals in the time domain by a sifting process. This process identifies all local extrema in the input signal, starting with those corresponding to the smallest oscillation period. Then, the identified oscillatory mode is extracted, which also yields the intermediate residual, as shown in Fig. 2. This oscillatory mode is called the intrinsic mode function (IMF). The identified extrema are used to construct upper and lower envelopes before being averaged to find the mean envelope. The mean envelope is then subtracted from the signal to acquire the oscillatory mode that consists of a spectral that is higher than the spectral of the derived mean envelope. A thorough explanation of how EMD operates is well presented by Zeller et al. in [15]. Generally, EMD segregates signal components locally and separates the data into locally non-overlapping time scale components.

From the decomposing eye blink region perspective, the first IMF is extracted from the signal, the intermediate residual is produced, and the sifting process is iterated again using the intermediate residual to extract other IMFs until it becomes a monotonic component. Consequently, the later extracted IMF has slower oscillatory characteristics than the former.

https://doi.org/10.31436/iiumej.v24i2.2814

This shows that EMD yields IMF components that start with the highest oscillatory rate to the final monotonic residual. Moreover, using the local extrema to derive the IMF allows the derivation to be automatic and adaptive time-variant filtering, which results from IMFs that exhibit non-stationarity nature with amplitude-frequency modulated (AM/FM) characteristics. As such, the nature of EMD sequential operations in filtering out IMFs can be approximated as a dyadic filter. This is because, on average, the amount of the extrema is reduced by one-half from an IMF to the next IMF.

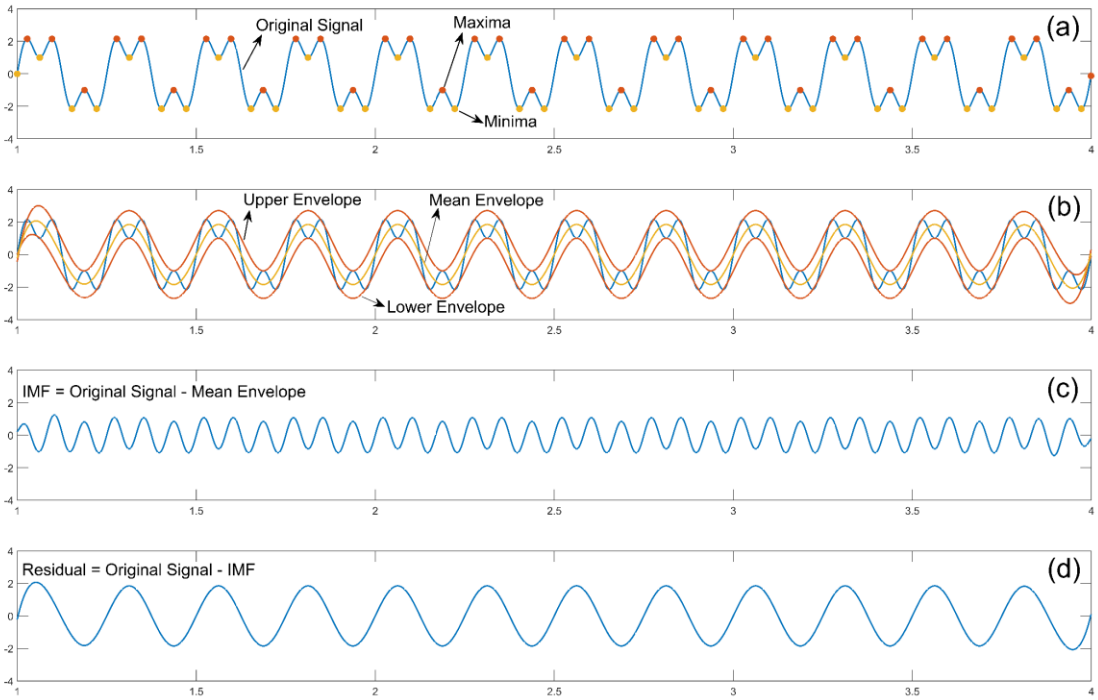


Fig. 2. The simplified sifting process visualization. (a) Extrema identification. (b) Mean envelope construction. (c) First IMF. (d) The residual, or the last IMF.

Since the advent of EMD, it has been integrated into the process of EOG artifact removal and has subsequently been widely disseminated in the academic literature. In [16], the correlation coefficient (CC) between the summed up IMFs with the true EEG component is used as an indicator for eye blink component presence, which is calculated after every time an IMF is added up from the first IMF. When the CC decreases to lower than 0.9, the latest IMF that is added up is deemed to have eye blink component. Hence, starting from that latest IMF to the residual, the IMFs are added up to reconstruct the eye blink component that can be used as a reference for adaptive noise cancellation (ANC). However, this technique needs the ground truth pure EEG that is similar in its temporal features to the EEG within the eye blink-contaminated data in order to calculate the CC value, which is counterproductive. While in [17], CC is also used between the artifactual EEG segment and the IMFs. Due to the scale of the eye blink component being larger than the EEG signal, the CC value obtained with IMFs containing eye blink component is larger. The CC threshold of 0.5 is used to discriminate between IMFs representing EEG and eye blink component, of which the IMFs with CC that is larger than 0.5 will be discarded before reconstruction. This method is vulnerable to the loss of some EEG components, especially the one that lies within the delta band. In [18], the 95% confidence interval of log energy of fractional Gaussian noise (fGn) is used as a threshold to select IMFs representative of EOG artifact. However, there is no workaround to deal with the potential of EMD's mode-mixing effect which would possibly cause some EEG component removal along with the reconstructed EOG.

The ability of EMD to decompose a signal into their respective oscillatory modes also makes it possible to employ multivariate data processing for a single EEG channel. For example, EMD is incorporated with canonical correlation analysis (CCA) in a way that the EMD is made to produce partial separation of eye blink artifact from the EEG data. The CCA is used to find the canonical weights that can be used to approximate the eye blink component that is free from EEG mixing [19]. Nevertheless, EMD can be utilized solely to extract the eye blink component without combining it with other techniques for its empirical method in decomposing the input signal.

We proposed using five samples window-mean thresholding to identify the eye blink regions within the single-channel EEG. Each identified region is then decomposed using EMD to extract the eye blink component. Thus, EMD is used only upon the isolated region as decomposing a time series with the transient component, which in this case is the eye blink component, causes mode-mixing due to over-sifting that may be induced during IMF derivation, as discussed by Zeller et al. [15]. Also, the EMD used for the proposed method is as proposed by Rato et al. [20], as its implementation addresses the problem of the EMD in terms of extrema computation, extrema interpolation, boundary conditions and sifting criterion.

2.3 Eye Blink Artifact Removal

Adaptive filtering is a filter which receives reference input $r_1(n)$ as its input impulse to find the least resultant error e(n) between the produced impulse response y(n) and the targeted component $r_2(n)$. An adaptive filter can be represented as an impulse filter as the following Eq. 1:

$$y(n) = \sum_k^L w_k \cdot r_1(n-k) \tag{1}$$

The parameter L is the order of the filter, w_L is the filter coefficient with span of L, r_1(n) is the reference input and y(n) is the impulse response.

The r_1(n) is useful as it is the essential factor in producing the impulse response that is converged to the desired component r_2(n) that is mixed with the input signal s(n). This is because the source of r_1(n) comes from the same source as $r_2(n)$. In the context of the interest, r_1(n) and $r_2(n)$ represent eye blink component. This means the eye blink component must be available to remove the respective eye blink artifact from the affected EEG segment.

In this paper, the eye blink component is extracted from the identified eye blink region in noisy EEG signals, as opposed to relying on the EOG channel which records the eye activities such as blinking and movement. The eye blink component extraction method is incorporated because of consideration for the ubiquity use of portable EEG in research and domestic uses. For the univariate method, eye blink removal is more plausible in its use of EEG data recorded using portable EEG devices as it only consists of a few EEG channels and many have no EOG electrode. Therefore, the eye blink removal method is designed to operate without the requirement for an EOG channel by extracting the eye blink component from noisy EEG. This extracted eye blink component is used as the reference r_1 in adaptive filtering.

In adaptive filtering, $r_2(n)$ removal is done by producing y(n) that is equivalent to the eye blink component within the EEG segment to not affect the EEG component during the removal. In order to find y(n), the error e(n) is used as feedback to assist the convergence of y(n). As shown in Eq. 2, the e(n) is the difference between the y(n) and $r_2(n)$ that is desired to be as small as possible, as the smaller the e(n) results better converged y(n), as depicted in Eq. 3.

$$e(n) = r_2(n) - y(n) \tag{2}$$

$$e(n) \approx 0,\ y(n+1) \approx r_2(n+1) \tag{3}$$

In order to cater for the next y(n) computation, the current e(n) is used as feedback into the adaptive algorithm. The adaptive algorithm optimizes the weight to converge the y(n+1) to $r_2(n+1)$, as being described in the following:

$$w_k(n+1) = w_k(n) - 2 \cdot \mu \cdot e(n) \cdot r_1(n-k) \tag{4}$$

The value of μ is between 0 and 1.

$$y(n+1) = \sum_k^L w_k \cdot r_1(n+1-k) \tag{5}$$

The weight optimization in Eq. 4 is based on the least mean square error (LMS) algorithm. The μ parameter is a constant to ensure fast adaptation for w_k(n+1) that can converge y(n+1) to $x_2(n)$ effectively.

In this paper, recursive least mean square error (RLS) is used for weight optimization because RLS needs lesser n iteration counts or steps number to converge the y(n) to its respective $r_2(n)$, hence a faster convergence rate. Faster convergence impacts its output, especially when the input is of a short segment. This applies to the marked eye blink region as its temporal length may span at most by only 2 seconds. The RLS algorithm is as the following:

$$w_k(n+1) = w_k(n) - 2 \cdot \mu \cdot e(n) \cdot K(n) \tag{6}$$

K(n) is the filter coefficient vector given by Eq. 7 as the following.

$$K(n) = \frac{P(n) \cdot r_1(n)}{\lambda + r_1^T(n) \cdot P(n) \cdot r_1(n)} \tag{7}$$

P(k) is the inverse correlation matrix with its initialization as the following:

$$P(0) = \begin{bmatrix} \delta^{-1} & 0 & \cdots & 0 \\ 0 & \delta^{-1} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \delta^{-1} \end{bmatrix} \tag{8}$$

The parameter δ is the regulatory factor and the constant k is the length of the tap input vector. The P(k) adaptation is done as depicted by the following equation.

$$P(n+1) = \lambda^{-1} \cdot P(n) - \lambda^{n-1} \cdot K(n) \cdot u^T(n) \cdot P(n) \tag{9}$$

The fact that P(n) and K(n) need each other during the weight optimization is why it is called a recursive least mean square adaptive algorithm.

3. METHODOLOGY

The implementation of the proposed method is described in this section. Fig. 3 illustrates the outline of the methodology in terms of the block diagram. Firstly, the procedure for EEG dataset preparation is described. Then, the eye blink region detection, eye blink component extraction and eye blink artifact removal are explained. Finally, the performance metric is calculated upon the removal output accordingly with the original simulated EEG data that is juxtaposed with the performance metric from Egambaram et al. [19] to prove the effectiveness of our method.

https://doi.org/10.31436/iiumej.v24i2.2814

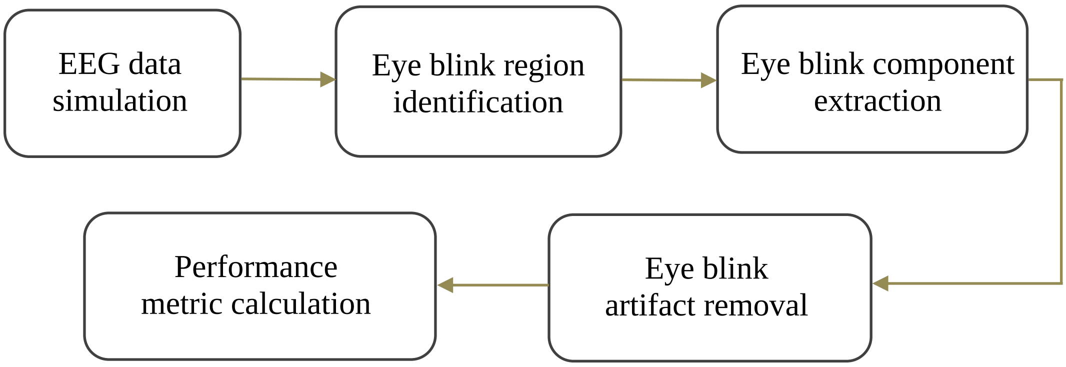


Fig. 3. The block diagram of a methodology for our eye blink removal

3.1 EEG Dataset Preparation

The EEG dataset used has been schemed to have an EEG component that can be ground truth data to assess the performance of the proposed method in preserving the brain-originated signals in the noisy EEG after eye blink artifact removal. Thus, EEG data is simulated by superimposing the pure EEG data with eye blink artifact. The superimposition of eye blink artifact can be understood as a linear mix between two signals:

$$X(t) = Y(t) + Z(t) \tag{10}$$

X(t) is the eye blink contaminated-EEG, while Y(t) is the pure EEG component and Z(t) is the eye blink artifact. The EEG data used in the experiment to assess the proposed technique is simulated in a way that it is possible to compare the performance metrics values, which is documented in [19]. Exponential functions represent the eye blink components Z(t) with different peak magnitudes that can be expressed mathematically as follows:

$$Z(t) = \sum Ae^{-(10t-B)^2} \tag{11}$$

A is the peak height ranges from 7 to 19 in magnitude and B is the temporal location of the peaks.

Fig. 4 (a) shows an example of the synthetic eye blink artifact. As for the EEG component, it is synthesized by using the pink noise for which its amplitude range between 0.0±3. Fig. 4 (b) illustrates the synthetic EEG, Y(t). In order to obtain a synthetic eye blink artifact contaminated-EEG, X(t), the synthetic eye blink component and synthetic EEG are added together as demonstrated by Eq. 10. Fig. 4 (c) depicts the synthetic X(t). This dataset is used to evaluate the equivalent performance metrics that later are used to compare with other EMD-based technique proposed by Egambaram et al. Every unit of Y(t), Z(t) and the resultant X(t) are simulated with the length of 10 seconds at 256 sampling rate or 2560 samples.

3.2 Eye Blink Region Detection

In order to extract the eye blink component, the eye blink regions and artifact-free regions within the EEG data need to be identified. The targeted processes only on the specified EEG regions not only reduce the computational requirement and time but also prevent the mode-mixing in the decomposed IMFs during eye blink component extraction by EMD. To be able to mark the eye blink region, amplitude thresholding is used to exploit the conspicuous difference of amplitude between pure EEG and eye blink artifact. In order to do so, the pure EEG maximum amplitude of the eye blink artifact-contaminated EEG needs to be ascertained beforehand. Accordingly, EEG data that is recorded or prepared that corresponds to the pure EEG component in the EEG of interest is computed as its maximum amplitude. This maximum

https://doi.org/10.31436/iiumej.v24i2.2814

amplitude value is a discriminatory factor in the eye blink artifact-contaminated EEG data. The following is a pseudocode to describe the steps in setting the amplitude threshold value:

Algorithm: Finding the threshold for the deflection detection algorithm for each EEG data channel.

Input: Array of pre-processed baseline EEG data, [data]

Output: Threshold for deflection detection

$[data_{mean}]$ ← mean([EEG_data(1:5:end)])

[data]min ← min($[data_{mean}]$)

[data]max ← max($[data_{mean}]$)

[value]max ← max(abs([data]max), abs([data]min))

threshold ← [value]max +1

From this pseudocode, the mean of every five-sample window in the EEG data is used to determine the threshold instead of the individual sample because this window-mean can act like smoothing against the outlier amplitudes from EEG high frequency-component that may wrongly influence the determination for the suitable threshold value. If the value of the threshold is too high, it may bypass the EEG segment that contains an eye blink artifact (false negative), but if it is too low, it may include a clean EEG segment (false positive). Fig. 5 (a) illustrates the threshold (red color) that discriminates the eye blink region and the clean EEG. In the case of EEG data used to test the proposed method, the synthetic EEG data Y(t) is used to compute the amplitude threshold.

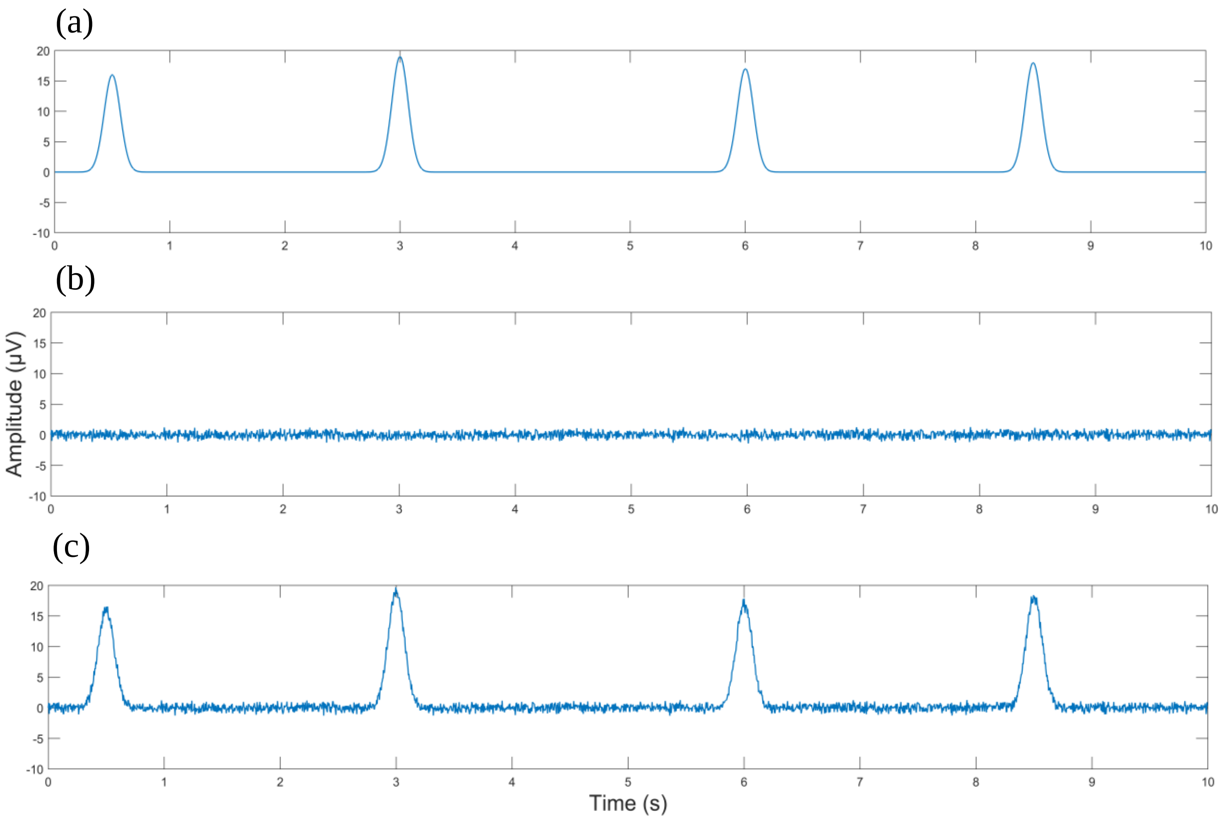


Fig. 4. (a) The simulated eye blink component Z. (b) The simulated EEG component Y. (c) The simulated eye blink contaminated-EEG X

As shown in the last line of the pseudocode, the threshold value is concluded as the maximum value added by 1 to dismiss clean EEG data samples effectively during eye blink artifact detection. During the detection, as visualized by Fig. 5 (b), the mean of every five samples is again computed and compared against the threshold to deem it as part of the eye blink region, as represented by an orange color or clean EEG samples (blue color) in a temporally successive manner. The detection by five-sample window-mean also helps to differentiate the five-sample segment whether it is a clean EEG sample or a contaminated EEG sample, more discretely.

The whole eye blink region is considered to be detected completely when no more 5-sample mean value is detected as an eye blink contaminated EEG segment for another 150 samples consecutively.

Before the detected eye blink-contaminated EEG samples are marked as a complete eye blink segment, the neighbouring samples at the beginning and end of the detected segment are included as part of the detected segment until the nearest zero-crossing is reached at both ends. At this point, an eye blink-region detection is complete. This is visualized in Fig. 5 (c), which shows that, in orange color, a complete eye blink region is marked. Then, the detection moves to the next five samples to detect another eye blink region.

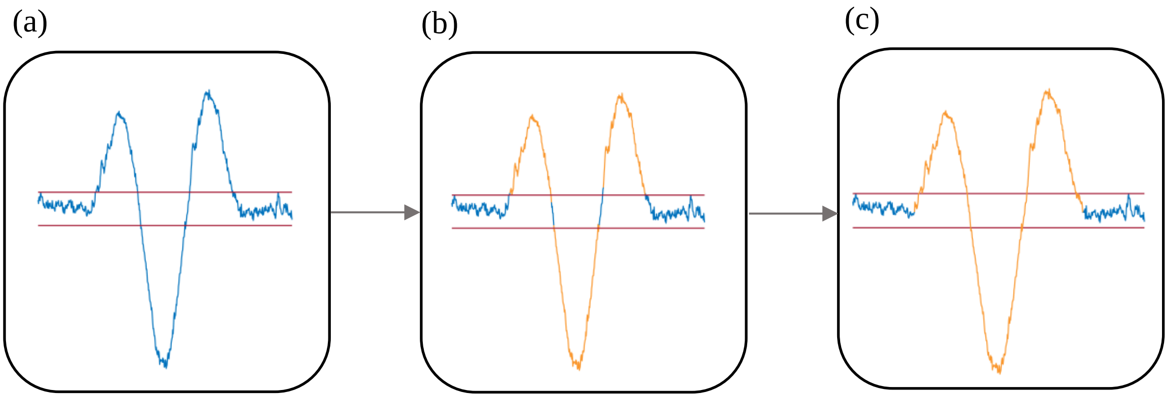


Fig. 5. (a) The window-mean threshold (red line) is used to discriminate the eye blink region. (b) Eye blink samples are detected (orange color). (c) The whole eye blink region is approximated by the nearest zero-crossing

3.3 Eye Blink Component Extraction

After the eye blink region is detected, EMD decomposes the segment. Before the decomposition, the segment is segregated into its individual deflection, as shown in Fig. 6 (b). To ensure smooth approximation of the envelope during sifting process, a constant α is used as a factor for the mean envelope e(t) whenever the e(t) is subtracted from the signal x(t) or the intermediate residual $r_n(t)$ as the following:

$$x(t) = x(t) - \alpha \cdot e(t) \tag{12}$$

The constant α value is between from 0 to 1.

Energy thresholding is deployed during IMF derivation and as a stopping criterion. For IMF derivation, qResol is used as an additional condition to derive an IMF. The threshold qResol is as an energy ratio of which when the energy of the e(t) is qResol times lower than the energy of x(t) or $r_n(t)$, the IMF is derived from the following:

https://doi.org/10.31436/iiumej.v24i2.2814

$$\text{If qResol} > \frac{\text{energy of } x(t) \text{or } r_n(t)}{\text{energy of } e(t)}, \text{ IMF is derived.} \quad (13)$$

Threshold qResol aims to avoid constructing envelopes that introduce new components during IMF derivation. As for the energy threshold for the stopping criterion, the ratio of x(t) or $r_n(t)$ to the new residual produced ($r_{n+1}(t)$), which is produced after an IMF is derived, called threshold qResid. The decomposition stops when the value of qResid is lower than its set threshold:

$$\text{If qResid} > \frac{\text{energy of } x(t) \text{or } r_n(t)}{\text{energy of } r_{n+1}(t)}, \text{ the decomposition is stopped.} \quad (14)$$

The incorporation of threshold qResid influences the decomposition by EMD so that it does not produce a monotonic signal as its final residuum in a definitive manner like the original EMD would. This behavior is useful when the objective of the decomposition is to extract low oscillatory components with specific temporal features.

Before the decomposition, the deflection segregation is done according to the zero-crossings between each deflection. Deflection segregation allows the eye blink component to be extracted by EMD without being fragmented across IMFs due to over sifting. Eye blink artifact morphology is independent of any mathematical basis. However, the individual deflection generally resembles a peak or valley with one extremum, which is consistent with the EMD final residuum of which, after being generated, the decomposition stopped. Hence, as illustrated in Fig. 6 (c), the final residuum is a representative of the respective eye blink deflection instead of the monotonic signal, which ultimately can be used to reconstruct the eye blink component directly without the need to utilize other IMFs for the process.

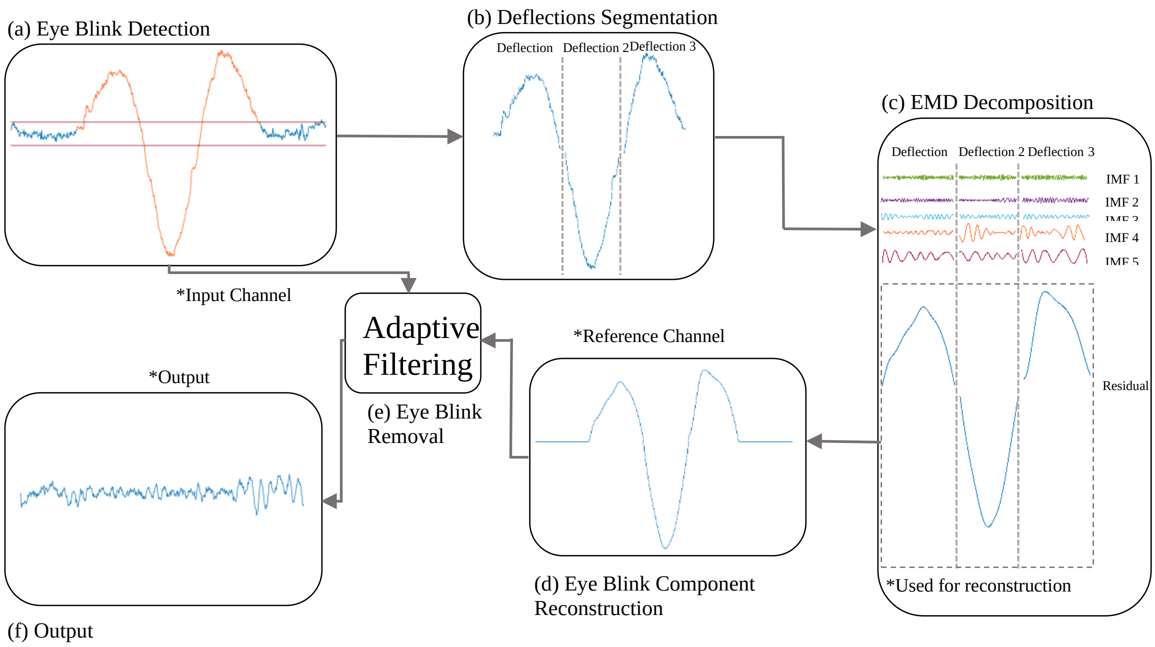


Fig. 6. (a) The identified eye blink region (orange line) is fed into EMD. (b) The eye blink is segregated into its individual deflection. (c) EMD decomposition. (d) Eye blink component extraction. (e) Eye blink artifact removal by ANC. (f) The ANC output is a cleaned signal.

The consistency of this occurrence is important so that only residuum is needed for the eye blink component reconstruction instead of the inclusion of a deliberate selection of suitable IMFs so that automatic eye blink component reconstruction is possible. In the proposed method, the residua are concatenated at their ends to form the respective eye blink component by means of spline interpolation, as visualized by Fig 6 (d). This reconstructed eye blink component has a similar deflection shape as the respective eye blink artifact contained in the EEG segment and thus can be utilized as a reference channel for adaptive filtering to remove the eye blink artifact from the EEG segment.

3.4 Eye Blink Artifact Removal

After the eye blink component is reconstructed, it is used as reference data $r_1(n)$, as shown in Fig. 7. The block diagram of the proposed adaptive filter that is used as adaptive noise cancellation (ANC) system is shown. The identified eye blink region is fed into the ANC as primary input d(n). The RLS-based algorithm is used in the adaptive filter to remove the eye blink artifact from the marked EEG segment. For the respective EEG segments that correspond to the eye blink affected EEG region, their length span ranges from 0.25 to 1.5 seconds. Hence, δ value is set to be 0.99 and λ value to be 10 with a coefficient order of 2 to ensure efficient and stable impulse response convergence.

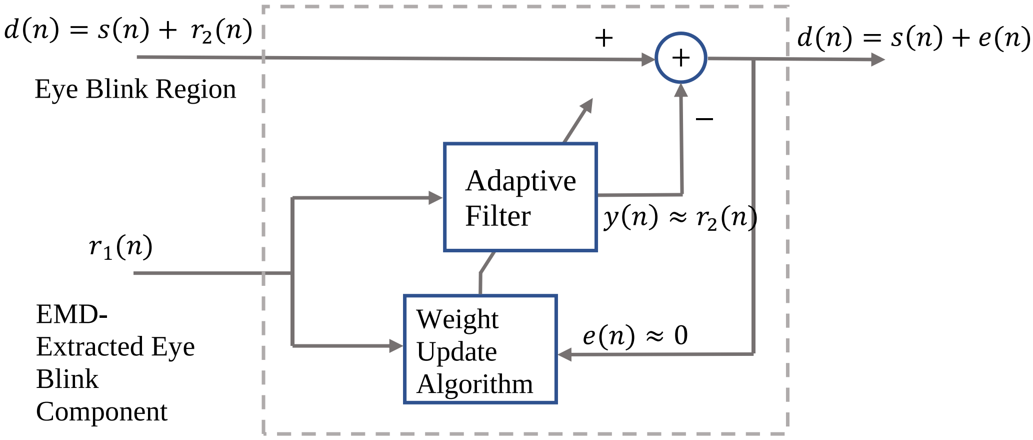


Fig. 7. ANC structure

3.5 Performance Metric

In order to measure the performance of the proposed method in removing the eye blink artifact, two data-centric measures are used on the processed EEG segments accordingly. The performance metrics are correlation coefficient (CC) and relative root-mean-square error (RMSE). The values generated from these performance metrics indicate how well the processed EEG data is preserved. The CC and RMSE are measured for the EEG component and eye blink component, respectively; between before and after being processed for eye blink artifact removal. The following are the mathematical descriptions of the performance metrics.

The CC is measured as the following:

$$CC_{EEG} = \frac{cov(Y_{pinknoise}, \ Y_{output})}{std(Y_{pinknoise}) * std(Y_{output})} \tag{15}$$

$$CC_{eye\ blink} = \frac{cov(Z_{simulated}, \ Z_{reconstructed})}{std(Z_{simulated}) * std(Z_{reconstructed})} \tag{16}$$

The RMSE is measured as the following:

$$RMSE_{EEG} = \sqrt{\frac{\sum_{t=1}^{n}(Y_{pinknoise}(t) - Y_{output}(t))^2}{n}} \tag{17}$$

$$RMSE_{eye\ blink} = \sqrt{\frac{\sum_{t=1}^{n}(Z_{simulated}(t) - Z_{reconstructed}(t))^2}{n}} \tag{18}$$

The variable $X(t)_{simulated}$ is the simulated eye blink contaminated-EEG, $Y_{pinknoise}$ is the simulated EEG component, Y_{output} is the cleaned simulated EEG component, $Z_{simulated}$ is the simulated eye blink component and $Z_{reconstructed}$ is reconstructed eye blink component.

4. RESULTS AND DISCUSSION

4.1 EEG Dataset Structure

The EEG dataset used to measure the performance metric is fully-simulated EEG data as described in Subsection 3.1. This is done to compare the performance metrics with the eye blink removal technique proposed by Egambaram et al. [19]. The generation of fully-simulated EEG for component Y(t), Z(t) and X(t) are iterated until 100 units are obtained. This total unit of EEG data is expedient to gauge the reliability of the performance metrics values in consistently proving the eye blink removal method of its level of performance.

4.2 Proposed Eye Blink Component Extraction

The extracted eye blink component is desired to be identical to its source. In this regard, a good eye blink component extraction is an eye blink component extraction with good precision of its features with the features of the original eye blink artifact. This is to ensure only the eye blink artifact is subtracted from the identified EEG segment during adaptive filtering. Generally, correct eye blink component extraction is also important for any rejection-based eye blink removal method, which includes the ICA-based method. Fig. 8 shows a sample of the reconstructed eye blink component (line in yellow colour) that being plotted in such a way that it can be compared with its respective eye blink reconstruction (line in blue colour). Two windows each magnifies a simulated eye blink region that originates from the main plot.

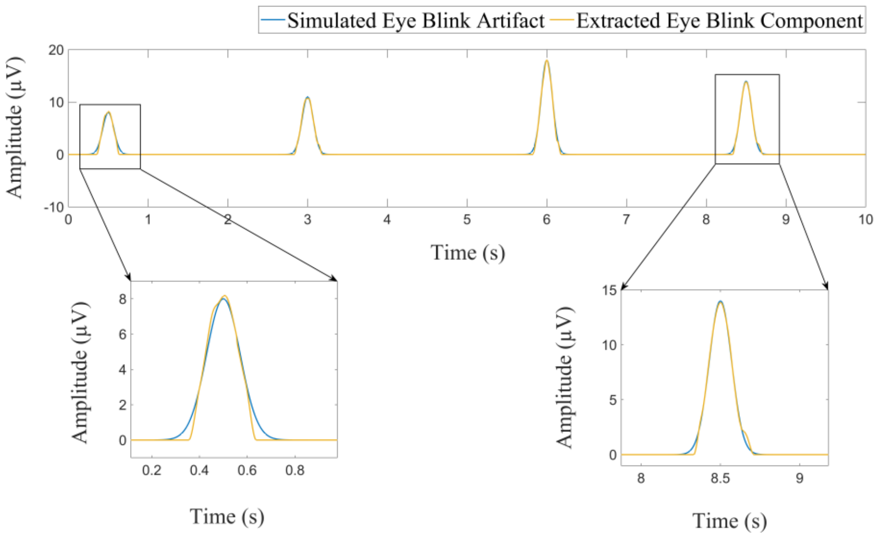


Fig. 8. The simulated eye blink component and its eye blink reconstruction.

The result shown in Table 1 contains the $CC_{eye\ blink}$ and $\mathrm{RMSE}_{\mathrm{eye\ blink}}$ values computed using the proposed eye blink component extraction method being juxtaposed with the respective performance metrics from the proposed FastEMD-CCA by Egambaram et al. The better value in comparison is bolded for every measurement.

Table 1: Performance metrics for eye blink component extraction between the proposed method and FastEMD-CCA.

Performance Metrics	EMD-AF (Proposed Method)	FastEMD-CCA
$\mathbf{CC_{eye\ blink}}(\boldsymbol{\mu} \pm \boldsymbol{\sigma})$	$\mathbf{0.9915 \pm 0.0358}$	0.9754 ± 0.0055
$\mathbf{CC_{eye\ blink}}$**(95% CI)**	**0.9880-0.9950**	0.9743-0.9765
$\mathbf{RMSE_{eye\ blink}}(\boldsymbol{\mu} \pm \boldsymbol{\sigma})$	$\mathbf{0.2960 \pm 0.2998}$	0.6580 ± 0.0776
$\mathbf{RMSE_{eye\ blink}}(\mathbf{95\%}\ \boldsymbol{CI})$	**0.2666-0.3253**	0.6426-0.6734

The result above shows that the eye blink reconstruction using EMD with spline interpolation resembles the original eye blink artifact better than the combination of EMD with CCA. Its CC value evidences this is statistically higher than FastEMD-CCA, while the proposed method's RMSE is statistically lower than that resulting from FastEMD-CCA. Hence, with appropriate energy thresholding for IMF derivation (qResol) and as decomposition stopping criterion (qResid), EMD is already substantial for excellent eye blink reconstruction. In the experimentation of implementing the EMD based on Rato et al. revision, α value is set to 0.5 for smooth but relatively efficient e(t) formation regulation, qResid is set to 55 for satisfactory IMF derivation and qResid is set to 57 for sufficient eye blink component extraction. Fig. 6 shows a sample of the simulated eye blink contaminated-EEG (line in orange colour) with its respective eye blink reconstruction (line in blue colour).

4.3 Proposed Eye Blink Removal

The extracted eye blink component is used to remove its eye blink source from its respective region. This can be done by means of component cancellation. In our proposed method, the extracted eye blink component is converged first by means of producing an appropriate impulse response using the RLS weight adaptation algorithm. The impulse response is then used to cancel out the eye blink artifact from the marked region by ANC. Fig. 9 displays the original simulated EEG component (line in red colour) being overlapped with its cleaned counterpart (line with yellow colour) to visualize any differences between them. The cleaned EEG is the output of the proposed method. Also, the eye blink-contaminated EEG (line with blue colour) is also plotted into the same graph to visualize the difference between it and the cleaned EEG.

In the following, the results on the performance metrics indicating the degree of possible change that may occur on the ground truth EEG are tabulated in Table 2. This degree of change is measured between the original simulated EEG data and the EEG data extracted after eye blink artifact removal performed by the proposed method. As for the metric, CC and RMSE are also used. The better value in comparison is bolded for every measurement. A higher CC value, closer to 1, or if it is 1 itself reveals that the cleaned segment is nearly or perfectly similar with its original counterparts. The lower value of RMSE points to a lower degree of difference between the cleaned segment and its original EEG component.

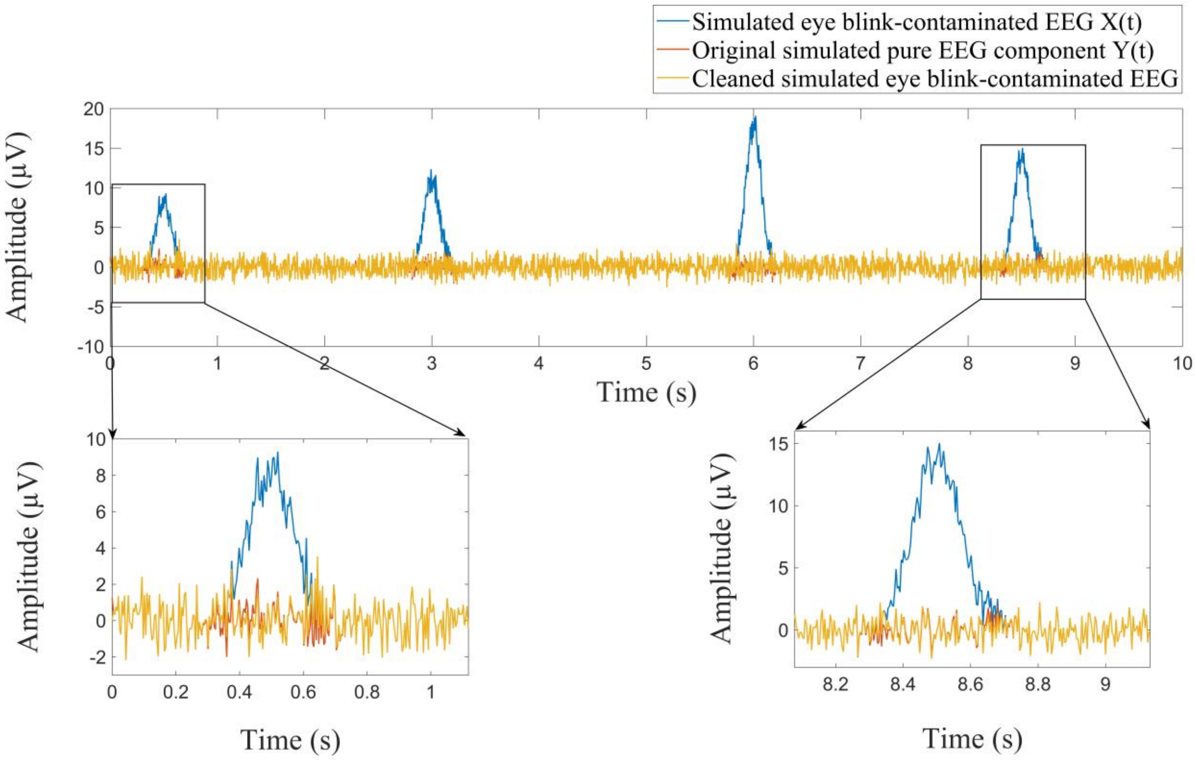


Fig. 9. The original simulated EEG data (line with blue colour) and its respective component retrieved after eye blink removal (line with yellow colour).

Table 2: Performance metrics for eye blink component removal between proposed method (EMD-AF) and FastEMD-CCA.

Performance Metrics	EMD-AF (Proposed Method)	FastEMD-CCA
$\mathbf{CC}_{EEG}(\boldsymbol{\mu} \pm \boldsymbol{\sigma})$	$\mathbf{0.9430 \pm 0.0839}$	0.7478 ± 0.0687
$\mathbf{CC}_{EEG}$**(95% CI)**	**0.9348-0.9513**	0.7341-0.7614
$\mathbf{RMSE_{EEG}}(\boldsymbol{\mu} \pm \boldsymbol{\sigma})$	$\mathbf{0.3211 \pm 0.2738}$	0.6580 ± 0.0776
$\mathbf{RMSE}_{EEG}(\mathbf{95\%}\ \boldsymbol{CI})$	**0.2942-0.3479**	0.6426-0.6734

The CC obtained from Egambaram et al. experimentation for the EEG component shows that its CC value dropped from the average of 0.9754, which is the CC obtained for the eye blink component, to 0.7478, which is the value that corresponds to the obtainment of ground truth EEG component after eye blink removal. This signifies that direct rejection of the eye blink artifact using its extracted eye blink component derived may cause distortion to the cleaned EEG segment. Therefore, it is substantial to introduce a mechanism that ensures the extracted eye blink component is converged to its eye blink artifact within the respective EEG segment in order to minimize the distortion that may be caused after the removal process. Adaptive filtering is serviceable on the matter of converging the extracted eye blink with the contained eye blink artifact. This is proven by the higher CC and lower RMSE value for the cleaned EEG segment by the adaptive filtering utilization in the proposed method.

FastEMD is meant not completely to decompose the EEG segment. Instead, it decomposes the respective EEG into a finite number of IMFs set beforehand, assuming that the first three IMFs are of EEG component and the remaining contains eye blink artifact. Subsequently, after the IMFs are divided into the non-artifactual and artifactual components, they are added up to reconstruct into two components: non-artifactual and artifactual. The CCA is later used to find the correlation between the two components to separate the EEG component that remains within the artifactual components.

This paper intended to test the capability of EMD in extracting the eye blink component that is similar in its temporal feature without being complemented by other data processing techniques. Its heuristic approach in signal decomposition is the desirable quality that is expected to be harnessed in retrieving specific components. Therefore, with an appropriate workaround to the EMD, like energy thresholding, EMD alone is effective for eye blink component reconstruction that is handy for its subsequent removal.

5. CONCLUSION

In this paper, we proposed the five samples-window mean as the basis for amplitude thresholding that was used to identify the eye blink region in the eye blinks-contaminated single-channel EEG. We demonstrated that incorporation of energy thresholds with EMD decomposition to extract the eye blink deflections makes it possible to automate the eye blink reconstruction process. The identified eye blink region and extracted components are used as reference in RLS-ANC system to remove the eye blinks artifact in eye blink region while preserving the original EEG in eye blink-free region. The notable contribution of the proposed method is the utilization of the data-driven decomposition nature of EMD to extract the eye blink deflections that is monumental in the eye blink component reconstruction. The proposed method is evaluated using synthetic EEG datasets, and results show better performance compared to existing fastEMD-CCA technique. The results show that the proposed method was successful in extracting eye blink components with high similarity to its simulated original waveforms and the removal of eye blink using ANC was successful without altering or distorting the original EEG. The results also demonstrated that EEG components decomposition and separation using EMD is sufficient for eye blink reconstruction without relying on the multivariate data processing methods that is significantly higher in complexity. In this study, eye blink identification and removal process were performed offline. For real time implementation, the routine for accommodating delay must be designed and incorporated adequately in distributive manner across the EEG recording and the eye blink removal process because the EMD decomposition process is intrinsically sequential. Nevertheless, the proposed method is a completely univariate eye blink removal method that extracts the eye blink component in an empirical manner which complements the adaptive denoising process for effective eye blink removal in a single EEG channel.

ACKNOWLEDGEMENT

This paper is funded by the Ministry of Higher Education (MoHE) Malaysia through the Research Management Centre, International Islamic University Malaysia (IIUM) under the Fundamental Research Grant Scheme FRGS 1/2019 (Ref: FRGS/1/2019/TK04/UIAM/02/14 – Project ID: FRGS19-098-0707).

REFERENCES

[1] Artoni F, Fanciullacci C, Bertolucci F, Panarese A, Makeig S, Micera S, Chisari C. (2017). Unidirectional brain to muscle connectivity reveals motor cortex control of leg muscles during stereotyped walking. Neuroimage, 159:403–416. doi: 10.1016/j.neuroimage.2017.07.013.

[2] Mandekar S, Holland A, Thielen M, Behbahani M, Melnykowycz M (2022). Advancing towards Ubiquitous EEG, Correlation of In-Ear EEG with Forehead EEG. Sensors,

22(4):1568. https://doi.org/10.3390/s22041568
[3] Lau-Zhu A, Lau MPH, McLoughlin G (2019). Mobile EEG in research on neurodevelopmental disorders: Opportunities and challenges. Dev Cogn Neurosci., 36:100635. doi: 10.1016/j.dcn.2019.100635.
[4] Nagar P and Sethia D (2019). Brain Mapping Based Stress Identification Using Portable EEG Based Device. 11th International Conference on Communication Systems and Networks (COMSNETS), 601–606. doi: 10.1109/COMSNETS.2019.8711009.
[5] Bhavnani S, Parameshwaran D, Sharma KK, Mukherjee D, Divan G, Patel V and Thiagarajan TC. (2022). The Acceptability, Feasibility, and Utility of Portable Electroencephalography to Study Resting-State Neurophysiology in Rural Communities. Front. Hum. Neurosci, 16:802764. doi: 10.3389/fnhum.2022.802764.
[6] Sawangjai P, Hompoonsup S, Leelaarporn P, Kongwudhikunakorn S, and Wilaiprasitporn T. (2020). Consumer Grade EEG Measuring Sensors as Research Tools: A Review. IEEE Sensors Journal, 20(8):3996–4024. doi: 10.1109/JSEN.2019.2962874.
[7] Shahbakhti M et al. (2021). VME-DWT: An Efficient Algorithm for Detection and Elimination of Eye Blink from Short Segments of Single EEG Channel. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29:408–417. doi: 10.1109/TNSRE.2021.3054733.
[8] Iwasaki M, Kellinghaus C, Alexopoulos A V, Burgess R C, Kumar A N, Han Y H, Lüders H O, and Leigh R J. (2005). Effects of eyelid closure, blinks, and eye movements on the electroencephalogram. Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology, 116(4), 878–885. https://doi.org/10.1016/j.clinph.2004.11.001.
[9] Kanoga S, Kanemura A, and Asoh H. (2019). Multi-scale dictionary learning for ocular artifact reduction from single-channel electroencephalograms. Neurocomputing, 347:240–250. doi: 10.1016/j.neucom.2019.02.060.
[10] Agarwal M and Sivakumar R. (2019). Blink: A Fully Automated Unsupervised Algorithm for Eye-Blink Detection in EEG Signals. 57th Annual Allerton Conference on Communication, Control, and Computing, Allerton, 1113–1121. doi: 10.1109/ALLERTON.2019.8919795.
[11] G Bhaskar N Rao, Anumala V S, Peri P P and Aneesh S. (2020). Automatic Detection and Correction of Blink Artifacts in Single Channel EEG Signals. International Journal of Advanced Computer Science and Applications (IJACSA), 11(1). http://dx.doi.org/10.14569/IJACSA.2020.0110144
[12] Jefri L A M, Rahman F A, Malik N A, and Isa F N M. (2022). Eye blink region detection in EEG using amplitude thresholding. 8th International Conference on Mechatronics Engineering (ICOM 2022), 77–83. doi: 10.1049/icp.2022.2269.
[13] Maddirala A K and Veluvolu K C. (2022). SSA with CWT and k-Means for Eye-Blink Artifact Removal from Single-Channel EEG Signals. Sensors, 22(3). doi: 10.3390/s22030931.
[14] Maddirala A K and Veluvolu K C. (2021). Eye-blink artifact removal from single channel EEG with k-means and SSA. Sci Rep., 11(1). doi: 10.1038/s41598-021-90437-7.
[15] Zeiler A, Faltermeier R, Keck I R, Tomé A M, Puntonet C G, and Lang E W. (2010). Empirical mode decomposition - An introduction. Proceedings of the International Joint Conference on Neural Networks, 2010. doi: 10.1109/IJCNN.2010.5596829.
[16] Shahbakhti M, Bavi M and Eslamizadeh M. (2013). Elimination of Blink from EEG By Adaptive Filtering without Using Artifact Reference. 2013 4th International Conference on Intelligent Systems, Modelling and Simulation, 190-194, doi: 10.1109/ISMS.2013.106.
[17] Patel R, Janawadkar M P R, Sengottuvel S, Gireesan K, and Radhakrishnan T S. (2016). Suppression of Eye-Blink Associated Artifact Using Single Channel EEG Data by Combining Cross-Correlation with Empirical Mode Decomposition. IEEE Sens J., 16(18):6947–6954. doi: 10.1109/JSEN.2016.2591580.
[18] Molla M K I, Rabiul Islam M, Tanaka T, and Rutkowski T M. (2012). Artifact suppression from EEG signals using data adaptive time domain filtering. Neurocomputing, 97:297–308.

doi: 10.1016/j.neucom.2012.05.009.

[19] Egambaram A, Badruddin N, Asirvadam V S, Begum T, Fauvet E, and Stolz C. (2020). FastEMD–CCA algorithm for unsupervised and fast removal of eyeblink artifacts from electroencephalogram. Biomed Signal Process Control, 57:2020. doi: 10.1016/j.bspc.2019.101692.

[20] Rato R T, Ortigueira M D, and Batista A G. (2008). On the HHT, its problems, and some solutions. Mech Syst Signal Process, 22(6):1374–1394. doi: 10.1016/j.ymssp.2007.11.028.